Systematic Bias Correction of Dynamical Seasonal Prediction using a Stepwise Pattern Project Method (SPPM)

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Abstract

Every dynamical seasonal climate prediction model has a systematic bias in their prediction data. Therefore, the predictive skill of dynamical models can be improved by reducing their systematic bias using dynamical or statistical post-processes. In this study, a new statistical model has been developed to empirically correct a dynamical seasonal prediction. The statistical model is developed based on the pattern projection method. The present model automatically selects predictor grids to avoid subjective selection for the predictor domain. To evaluate the statistical model, statistical correction with the present model is applied to SST prediction data produced by a coupled GCM. After statistically correcting the dynamical SST prediction, the predictive skills are improved over most regions and most lead times. In particular, the SST predictions over the western Pacific and Indian Ocean are significantly improved where the coupled GCM has a large systematic bias.

1. Introduction

During the last few decades, many studies have been devoted to modeling and predicting climate variability, in step with increased scientific and economic interest in seasonal climate prediction and predictability. Since Zebiak and Cane (1987) made a breakthrough in predicting El Nino/Southern Oscillation (ENSO), the major source of the Earth climate predictability, the improvement in dynamical seasonal prediction has accelerated. Before the 21st century, statistical predictions were generally better than dynamical ones despite the fact that dynamical predictions are based on the most scientific grounds (Van den Dool 1994; Barnston and Smith 1996; Anderson et al. 1999; Zorita and von Storch 1999). However, the major operational prediction centers have recently reported that dynamical prediction is comparable to (or even better than) statistical prediction, which has a long history back to early 1900s (van Oldenborgh et al. 2003 for European Centre for Medium-Range Weather Forecasts (ECMWF) system; Saha et al. 2006 for National Center for Environmental Prediction (NCEP) system).

Some meteorological centers worldwide have implemented routine dynamical seasonal predictions using coupled atmosphere-ocean models, such as ECMWF, NCEP, and the Bureau of Meteorology Research Centre (BMRC) (Palmer et al. 2004; Saha et al. 2006; Wang et al. 2002), promoted by a rapid growth in computing resources and the improvement of coupled models. However, the state-of-the art coupled models still have systematic errors that degrade seasonal climate prediction (Wang et al. 2007; Lee et al. 2007; Jin et al. 2007; Kug et al. 2007a), indicating that statistical post-processing is still needed.

Widely used methods for statistical correction in climate prediction include an analog method, various coupled pattern methods, regression methods, and a neural network (Graham et al. 1994; Kim and Kang 1997; von Storch et al. 1993; Zorita et al. 1995; Zorita and von Storch 1999; Sailor and Li 1999; Ward and Navarra 1997; Feddersen et al. 1999; Kang et al. 2004; Kug et al. 2004, 2007b). In particular, it has been well demonstrated that the leading modes of systematic error in dynamical models can be corrected by a statistical relationship between the prediction and observed anomalies, the so-called coupled pattern technique (Graham et al. 1994). The most commonly used methodologies of this technique are based on singular value decomposition analysis (SVDA) (Ward and Navarra, 1997; Kang et al. 2004) and canonical correlation analysis (CCA) (Barnett and Preisendorfer 1987; Barnston 1994; Feddersen et al. 1999). Feddersen et al. (1999) demonstrated that post-processed results are not sensitive to any choice among methods based on the CCA, SVD, or EOF decompositions. However, Kang and Shukla (2006) noted that the SVD-based correction method cannot correct a bias which is not related to leading SVD modes and/or has a local character.

Kang and Shukla (2006) and Kug et al. (2007b) introduced a kind of point-wise regression method based on pattern projection (PPM) in order to correct systematic bias in predicted precipitation anomalies for the former and to predict SST for the latter. While the conventional regression models for statistical forecasting use the time series of the area-averaged predictor (Lee et al. 1999; Blender et al. 2003; Kug et al. 2004) or the EOF principle components of the predictor field (Colman 1997; Colman et al 1999), the PPM method is based on the large-scale patterns of predictors correlated to the local (grid point) predictand. Kang and Shukla (2006) showed that PPM is effective in improving the forecast skill of dynamical seasonal prediction, especially over land areas compared to SVD method. Kug et al. (2007b) showed that the PPM method has a better skill than other SST prediction models used in their study over the Western Pacific region.

In this study, a newly designed PPM method was developed, referred to as the Stepwise Pattern Projection Model (SPPM). To test this statistical model, the SPPM is applied to dynamical SST prediction data produced by a coupled GCM.

In section 2, we introduce the data and models used in this study. The results of statistical correction are presented in section 3 and the sensitivity of the prediction skill to the prediction sample number discussed in section 4. Section 5 gives a brief summary and discussion.

2. Data and Model Description

a) DATA

The NCEP SST data were utilized both for construction of the statistical model and verification of the prediction. The data were reconstructed using empirical orthogonal functions (Smith et al. 1996) for the period 1950-95, and optimum interpolation (Reynolds and Smith 1994) for the period 1996-2003. The data period used in this study is the 54 years from 1950 to 2003. The SST data were interpolated to a 5^{o} latitude X 5^{o} longitude grid to focus on a spatially large scale SST variation.

b) Coupled GCM prediction

In this study, a coupled GCM is used for dynamical seasonal prediction. The present coupled GCM was developed at Seoul National University (SNU). The atmospheric component of the coupled GCM is SNU atmospheric GCM (AGCM). The AGCM is a spectral model with a triangular truncation at wave number 42 and has 20 vertical levels. The physical processes included are the Nakajima two-stream scheme for longwave and shortwave radiation (Nakajima et al. 1995), the Relaxed Arakawa-Schubert scheme (Moorthi and Suarez 1992), shallow convection, land surface processes, gravity wave drag, and planetary boundary layer processes (Kim 1999). Kim (1999) showed that the SNU GCM reasonably simulates the climatological mean patterns of tropical circulation and their anomalies during El Nino.

The oceanic component is version 2.2 of MOM2 Oceanic GCM developed at the Geophysical Fluid Dynamic Laboratory. The model is a finite difference treatment of the primitive equations of motion using Boussinesq and hydrostatic approximations in spherical coordinates. The model domain includes most global oceans, and the coastline and bottom topography are realistic. The zonal resolution is 1.0 degrees. The meridional grid spacing is 1/3 between 8^{C}S and 8^{C}N, gradually increasing to 3.0 at 30^{C}S and 30^{C}N and fixed at 3.0 in the extratropics. There are 32 vertical levels with 23 levels in the upper

450m. The model uses the Noh and Kim (1999) mixed layer model for vertical diffusion to improve the climatological vertical structure of the upper ocean.

The ocean model communicates once a day with the atmospheric model. Two component models exchange SST, wind stress, freshwater flux, longwave and shortwave radiation, and turbulent fluxes of sensible and latent heat. No flux correction is applied. Though no flux correction is applied, the model does not exhibit any significant climate drift in the long-term simulation. In addition, the present coupled GCM simulates reasonably the climatology of most of the oceanic and atmospheric variables.

Using the SNU coupled GCM, dynamical seasonal prediction has been carried out. To obtain oceanic initial conditions, the ocean component of the CGCM is integrated by prescribing observed SST and wind stress as surface boundary conditions. The atmospheric and land initial conditions are obtained from NCEP reanalysis data (Kalnay et al. 1996). Given the initial conditions, the experimental predictions are carried out with 6-month lead time, starting from May 1st for the years 1960-2001. Six ensemble members are generated with slightly different initial conditions, and their ensemble mean is used for the statistical correction in this study.

c) Stepwise Pattern Projection Model (SPPM)

A Stepwise Pattern Projection Model, hereafter referred as "SPPM", is a kind of pointwise regression model. The predictor of the model is a pattern of a model variable in a certain domain and the predictand is SST at each grid point over the global Ocean. In this study, the SST predicted by a coupled GCM is used for the predictor variable. The main idea of the model is to produce a prediction of the predictand grid by projecting the predictor field onto the covariance pattern between the large-scale predictor field and the one-point predictand. The model equation is as follows:

$$
\begin{aligned}
&SST(t_f) = \alpha \cdot P(t_f) \\
&\alpha = \frac{\frac{1}{T}\sum_t^T SST(t)\cdot P(t)}{\left[\frac{1}{T}\sum_t^T P^2\right]} \\
&P(t) = \sum_x^D COV(x)\cdot \Psi(x,t) \\
&COV(x) = \frac{1}{T}\sum_t^T SST(t)\cdot \Psi(x,t)
\end{aligned}
\qquad (1)
$$

where x and t denote spatial and temporal grids, respectively. P indicates a time series projected by the covariance pattern between predictand, $SST(t)$, and predictor field, $\Psi(x,t)$, in a certain domain (D). The parameter, α, is a regression coefficient of the projected time series, P, on the predictand SST during a training period, T. In this study, we adopted the training period as 41 years in the cross-validation process.

In this statistical prediction, selection of the predictor domain (D) plays a crucial role in the predictive skill. In general, traditional pattern projection models use a fixed geographical domain whose location and size are not varied for the predictor during whole forecast period. This method is appropriate for regional climate prediction, where the number of predictands is limited. Sometimes, the predictor domain is subjectively selected in order to artificially increase the forecast skill. However, when the prediction target covers a wide region so that the number of predictands is large, it is difficult to choose the predictor domain subjectively. Therefore, in this study, a new method is adopted in order to select the prediction domain objectively and to obtain an optimal predictive skill for each predictand grid. In the SPPM process, the optimal predictor domain is automatically selected with objective criteria.

The SPPM consists of two steps to obtain a final prediction. The first step is a selection of the predictor domain, and the second step is a prediction by the pattern projection of Eq. (1). In the first step, to select the predictor domain, correlation coefficients between a predictand and a two-dimensional candidate variable for predictor are calculated to search the possible predictor domain. Among all possible grids, the grids having a relatively high correlation are selected as a predictor grid. In this case, the selected grids can be split into several regions. In the tradition statistical model, only one geographical domain should be selected as the predictor domain, so other grids beside that selected cannot be used. However, in the SPPM, all grid points are gathered and a reconstructed domain is constructed by lining up the selected grid pints. The reconstructed domain is regarded as a predictor domain. How can we determine the selected grids among whole grids? The whole grids are firstly classified into several groups by their correlation coefficients during the training period. The criteria for grouping are correlations 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, and 0.1 with the predictand during the training period. First of all, only grids in the first group (more than correlation 0.8) are used as a reconstructed domain. When the grid number of the first group is less than 100 grid points, the second group is also included as a reconstructed domain. Similarly, if including the nth group does not give enough grid numbers, the (n+1)th group is used. As a result, high correlation regions encountered during the training period are selected as reconstructed domains. If the grid numbers are not enough in spite of using all the groups, the model predicts the climatological value as a final prediction. Once the predictor domain is selected, the statistical prediction is carried out by pattern projection from Eq. (1).

3. Statistical Correction

Dynamical seasonal prediction is performed for the 42 years 1960-2001 using SNU coupled GCM. Figure 1 shows the forecast skill of the dynamical prediction for summer (JJA) mean SST. The summer mean has a 2-4 month lead forecast since the prediction starts from 1st May. The coupled GCM has a high predictive skill over the ENSO region. The correlation is more than 0.8 over the central and eastern Pacific. In addition, the model has a predictive skill over the tropical Atlantic Ocean and north Indian Ocean. For these regions, the RMS errors are smaller than their standard deviation. However, the coupled GCM has a low predictive skill over the warm pool region. In particular, over the eastern Indian Ocean, the correlation skill is very poor and the RMS error is significantly larger than its observed standard deviation. This implies that the coupled GCM has a serious bias in these regions.

Though the model has difficulty in predicting local variability exactly at each grid, the model may capture large-scale signals related to the local variability outside of the grid. In that case, the predictand is likely to be predictable by applying a simple statistical correction method, as long as we can find those signals from the predicted field. This idea is the basis of the present statistical model. For example, for the grid point at 80^{o}E and the Equator, the model has a poor prediction skill. The correlation skill is nearly zero with a 3-month forecast lead-time. However, the model simulates large-scale signals which are significantly correlated with the predictand. Figure 2a shows the correlation coefficients between the observed SST at 80°E and the Equator, and the SST predicted by the coupled model with a 3-month lead-time. As expected, the correlation coefficient between the observed and predicted SST is very low at the same grid. However, significant correlations are found over several regions. In particular, the correlation is high over most of the Indian Ocean except for the equatorial central and eastern Indian Ocean. This indicates that the model has a systematic bias over the equatorial Indian Ocean. Also, high correlation regions exist over the off-equatorial eastern Pacific and tropical Atlantic Ocean. The correlation is more than 0.6 over those areas. This implies the possibility of improveing prediction of the predictand by using the significantly correlated SST predictions over those grids as a predictor rather than using the direct model prediction at the same grid.

The SPPM was applied to the dynamical prediction in order to realize the above idea. As explained in Section 2, the SPPM firstly finds optimal predictor grids, and then predicts the local predictand by applying the pattern projection to the selected predictor grids. Figure 2b shows one example of grid selection for a predictor area. Because we use cross validation, the selected predictors are changed for every year's prediction. So, we counted a number of the selected predictor grids in the cross validation procedure. Figure 2b shows the counted number when the SPPM predicts the SST at 80°E and the Equator. Since total 42-year predictions are used, the maximum number will be 42. In most cases, the predictors are selected over the Indian Ocean and the equatorial Atlantic Ocean, as shown in Fig 2b. These regions are consistent with the high correlation region in Fig. 2a. However, few grid points over the off-equatorial Pacific are selected as predictor grids though the correlation coefficient is high. This indicates either that the relation is not stable or that the high correlation comes from a strong concurrence of a few cases. Therefore, those grid points are not appropriate as predictor grids.

Figure 3 shows another example of the SPPM procedure for the SST at 140°W and the Equator. For the SST at this grid point, the dynamical model has a predictive skill over a 6-month lead-time. Therefore, the observed SST at this grid point is correlated with the model SST prediction over the equatorial central Pacific, including the predictand grid. The predictor grids in SPPM are mostly selected over the central Pacific. These grid points are well matched to the high correlation region as shown in Fig 3a. From two examples, it can be seen how the SPPM searches the predictor grids properly.

Using the SPPM, the dynamical prediction is statistically corrected for 1-6 month lead forecast data. Figure 4 shows the correlation skill and RMS error of the summer mean (JJA) SST corrected by the SPPM. Compared to the uncorrected prediction (Fig. 1), the skill of the statistical correction is improved over most of the regions. For the ENSO region, the improvement for the equatorial SST seems not to be significant. However, over the off-equatorial Pacific the SST correction is largely improved. Because the model predicts SST anomalies too narrowly associated with ENSO, the simulated ENSO SST pattern is somewhat different from the observed pattern. That is, there is some systematic bias in the off-equatorial region. Because the statistical correction reshapes the SST pattern associated with ENSO, the prediction skill can be improved after the correction.

A distinctive improvement in the statistical correction is found over the warm pool region. Note that the dynamical SST prediction has a very poor skill over the warm pool region. In particular, the eastern Indian Ocean SST prediction has a large bias in its dynamical prediction, even though the lead-time is short. However, the Indian Ocean SST is correlated with the tropical Pacific SST in its observational data (Klein et al. 1999; Xie et al. 2002; Kug et al. 2004). Therefore, if the model predicts ENSO SST well, then the Indian Ocean SST can be statistically predictable to some extent. After statistical correction with the SPPM, the SST prediction is greatly improved. Over most of the warm pool regions, the correlation becomes greater than 0.6, and the standardized RMS error becomes less than 0.8.

In order to easily show the improvement in the statistical correction, three SST indices are defined and used. They are NINO3.4 SST, Western Pacific (WP) SST, and Indian Ocean (IO) SST. Their definitions are listed in Table 1. Using the three SST indices, correlation skills are calculated and compared for 1-6 month lead time forecasts. For NINO3.4 SST prediction, the skill is slightly improved but the difference is not significant, as mentioned before. In this region, the SPPM selects the predictor grid mostly among the nearest grids from the predictand grid. Therefore, the correction is not effective and it has a similar skill to the uncorrected prediction.

For the WP SST, the skill of the uncorrected prediction suddenly degrades as soon as the prediction starts, but recovers for 5-6 month lead times. This may be related to the seasonality of the prediction skill. However, the corrected prediction has a similar skill for 2-6 month lead times and it is always better than the uncorrected prediction and greater than a correlation of 0.5. For the IO SST, the skill of the uncorrected prediction is rapidly degraded as the lead-time gets longer. For a 6-month lead-time, the correlation is nearly zero, while, after

SPPM correction the prediction skill is greatly improved. The skill is slowly degraded as the lead-time gets longer but the correlation is larger than 0.6 even at 6 month lead-time.

4. Sensitivity to the number of the prediction sample

In the previous section, we have shown that statistical correction with SPPM improves the forecast skill by reducing systematic errors in dynamical predictions. In the SPPM process, it is very important to choose optimal predictor grids, which are related to the variability of the predictand. If the predictor grids are commonly selected for every year's prediction, it would be expected that the statistical correction works well. However, if the selected predictor grids are largely changed for each year's prediction, the statistical correction will have a poor skill. As explained before, the predictor grids are selected by their correlation with the predictand during the training period. In this case, the length of the training period is critical to the stable selection of the predictor grid in the cross-validation procedure, because a short training period can easily produce an artificially high correlation. So far, many dynamical seasonal prediction studies have carried out the hindcast for about the recent 20 years. In this case, it may be difficult to obtain a stable predictor or stable statistical relationship when the statistical correction is applied. Because the present study uses a relatively long historical forecast (42 years), it gives a must better chance of testing the dependency of the forecast skill with statistical correction on the length of the training period.

To test this, statistical correction using the SPPM is repeated with different training periods. The dynamical prediction has 42 samples for 1960- 2001. Among them, the SPPM is applied using 32 samples for the years 1970-2001, and 22 samples for the years 1980-2001. These results are compared to that with 42 samples. The forecast skill is calculated only for the period of 1980-2001 for fair comparison. Figure 6 shows the correlation skill with different sampling numbers. When the 32 samples are used, the skill is generally degraded compared to those of the 42 samples but the difference strongly depends on the region considered. Over the eastern and off equatorial Pacific, and the Atlantic Ocean, there is no significant change, indicating that the statistical correction is insensitive to the number of samples in these regions. Note that the dynamical correction already has a good skill in this region. Therefore, the SPPM selects a predictor from neighboring grids in these regions, so the selection of the predictor is relatively stable regardless of the number of samples.

A distinctive impact of the number of samples appears over the warm pool region, where statistical correction significantly improved the dynamical prediction. In particular, the correlation skill over the western Pacific is degraded more than 0.1 when the 32 samples are used. This indicates that the selection of the predictor in the SPPM is sensitive to the number of samples in this region. In addition, the correlation is also significantly reduced over the southern subtropical regions. Interestingly, the degradation of the correlation skill over the eastern Indian Ocean is relatively small, even though the original dynamical prediction was very poor. This implies that the error for the eastern Indian Ocean SST is systematic and the selected predictors are not sensitive to the number of samples. When only 22 samples are used, the differences become clearer. Except for the off-equatorial Pacific and Atlantic Ocean, the skill is significantly degraded. It is likely that the difference from the results of the 42 samples is larger where the original dynamical prediction is poor. In particular, the difference is more than a correlation of 0.3 over the warm pool region. The correlation skill is even lower than that of some regions over the western Pacific. This sensitivity experiment shows that the statistical stability is very critical to the forecast skill of the statistical correction. In addition, the results support the idea that a 20-year hindcast of seasonal climate prediction is not sufficient for the statistical post-process, and a longer hindcast integration should be required to obtain a better forecast skill.

4. Summary and Discussion

A new statistical model has been developed based on the pattern projection method in the present study. To avoid subjective selection for the predictor domain, the present model automatically selects the predictor grids based on their statistical relationship during the training period. To validate the model, the present model is applied to dynamical seasonal prediction data. The state-of-art coupled models predict reasonably large-scale climate phenomena such as ENSO, Indian Ocean warming, and the Pacific North America (PNA) pattern, but they have some difficulties in capturing their detailed structure and pattern. Therefore, the forecast skill for local grid points can be poor. Because the main idea of the present model is to predict local grid points from large-scale patterns, seasonal climate prediction data are good to test the performance of the present model. Using the SPPM, the SST prediction produced by the SNU coupled GCM has been statistically corrected. After the statistical correction, the prediction skills show an improvement over most regions and most lead-times. In particular, the SST predictions over the western Pacific and Indian Ocean are significantly improved, while the coupled GCM has a poor prediction skill over those regions.

So far, many statistical models have been developed to predict regional climate (Barnett and Preisendorfer 1987; Livezey et al. 1994; van den Dool 1994; Colman 1997; Lee et al. 1999). In most cases, they firstly select optimal predictors from empirical or intuitive relations with the predictand before the prediction process is developed. Therefore, the selection of the predictors can be subjective. Sometimes, it can cause an absurdly high skill for a testing period because the relationship between predictor and predictand is implicitly considered in selecting the predictor without incorporating an exclusion process in the testing period, like cross-validation. In this case, the model skill is markedly degraded in operational prediction compared to that in the testing period due to the so-called overfitting problem. In addition, these statistical models have difficulty when other predictands are applied because the optimal predictors will be changed. If the number of predictands is large, the subjective selection method for predictors is not applicable. Therefore, an automatic process for selecting predictors is developed in this study. Because the predictor is automatically selected by a cross-validation process, the present model can escape the overfitting problem. Also, the model would be easily applicable to different kinds and large numbers of predictands without specified considerations.

The skill of statistical models strongly depends on how the model captures the actual signal of the relationship between predictor and predictand from limited available data. If the number of sample data is unlimited and the training data of the statistical model are infinite, it is easy to capture the actual signal of the relationship. In this case, the statistical relation and the parameters in the statistical model are quite stable. This means that the statistical relation and parameters used in real prediction are mostly identical to those in the training period. Accordingly, a skillful prediction is expected. In the case of post-processes of dynamical seasonal prediction, such as statistical correction, downscaling and multi-model ensembles, the training data will be historical hindcast data. Because most operational centers have hindcast data starting from early 1980, the sample data for the training period are necessarily less than 30. In this study, the statistical correction is sensitive to the training period. Except for the ENSO region, we have shown that the skill of a statistical model is significantly degraded as the sample number is reduced. This indicates that the current less than 30-year hindcast data in seasonal prediction is not sufficient to create stable relations in the statistical model. Therefore, improvement in the statistical post-processes will be limited. In conclusion, the current skill of the seasonal prediction can be easily improved by simply increasing the hindcast data.

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Figure Legends

Figure 1. a) Correlation coefficients and b) RMS error between JJA SSTs of dynamical model prediction and observation. The RMS error is divided by the interannual standard deviation of SST at each grid.

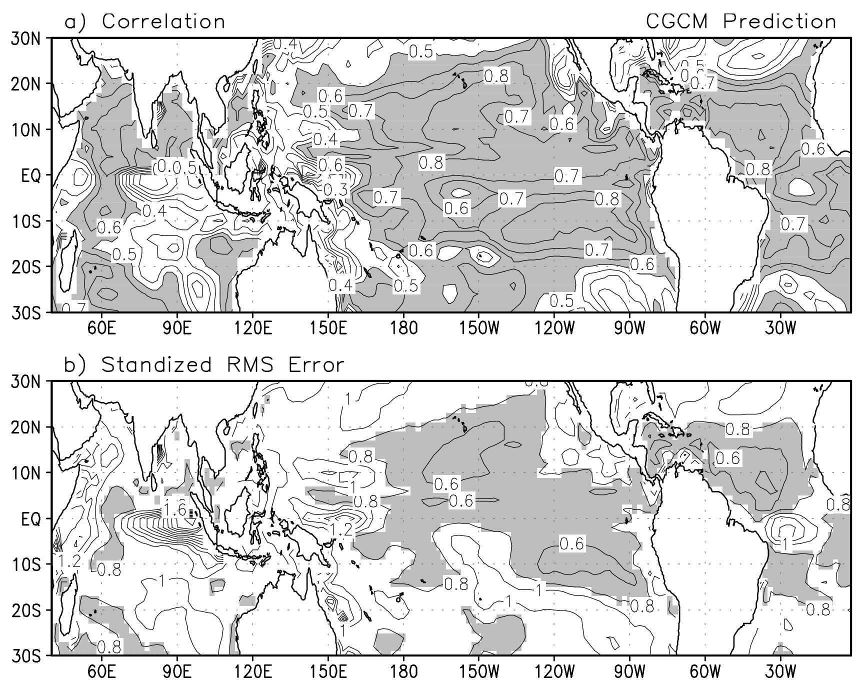
Figure 2. a) Correlation coefficients between 6-month lead SST predictions and observed SST at 80E and the Equator. b) Selected number as a predictor for SST at 80E and the Equator in SPPM prediction process. Details are referred to in the text.

Figure 3. The same as Fig. 2 except for SST at 140W and the Equator.

Figure 4. The same as Fig. 1 except for SST corrected by the SPPM

Figure 5. Correlation skills of dynamical model prediction (dashed line) and statistical correction (solid line) for a) NINO3.4 SST, b) Western Pacific SST and c) Indian Ocean SST.

Figure 6. Correlation skills (contour) of the statistical correction (shaded) for the period of 1980-2002 when a) 42-year data, b) 32-year data and c) 22-year data are used as the training data. The shaded areas indicate the correlation difference from the correlation shown in Fig. a).



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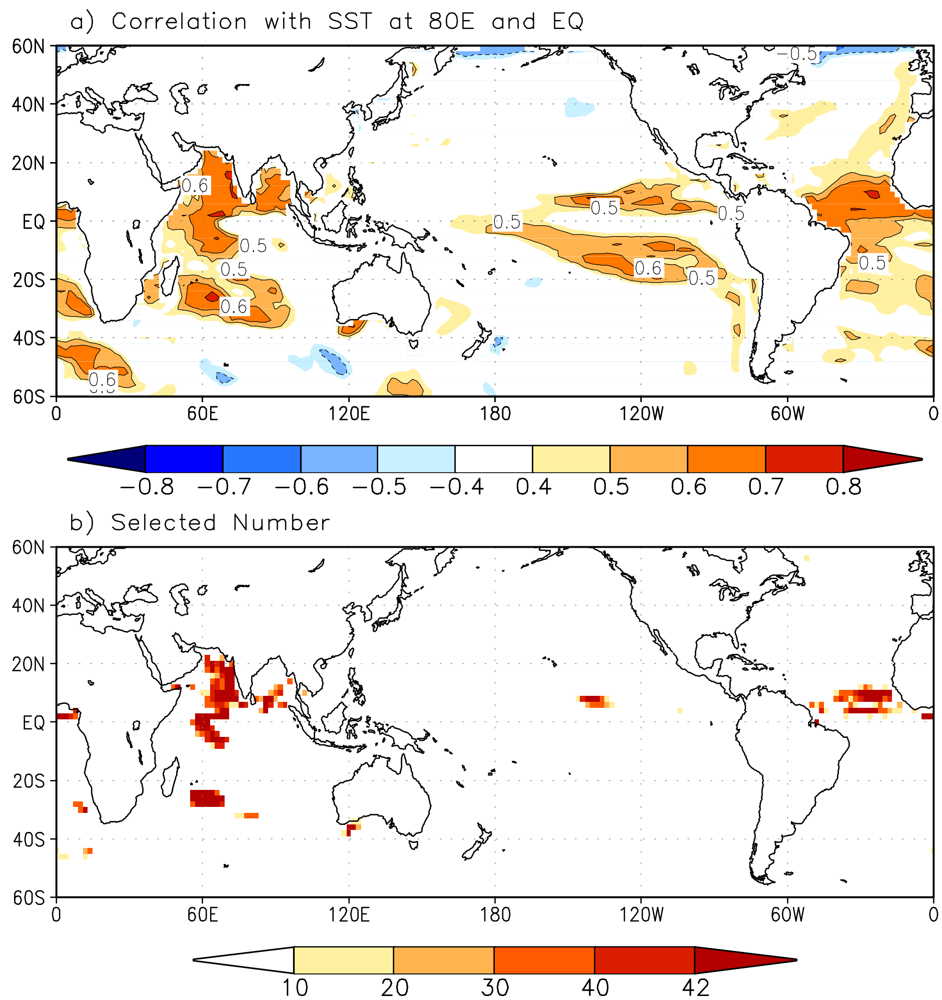

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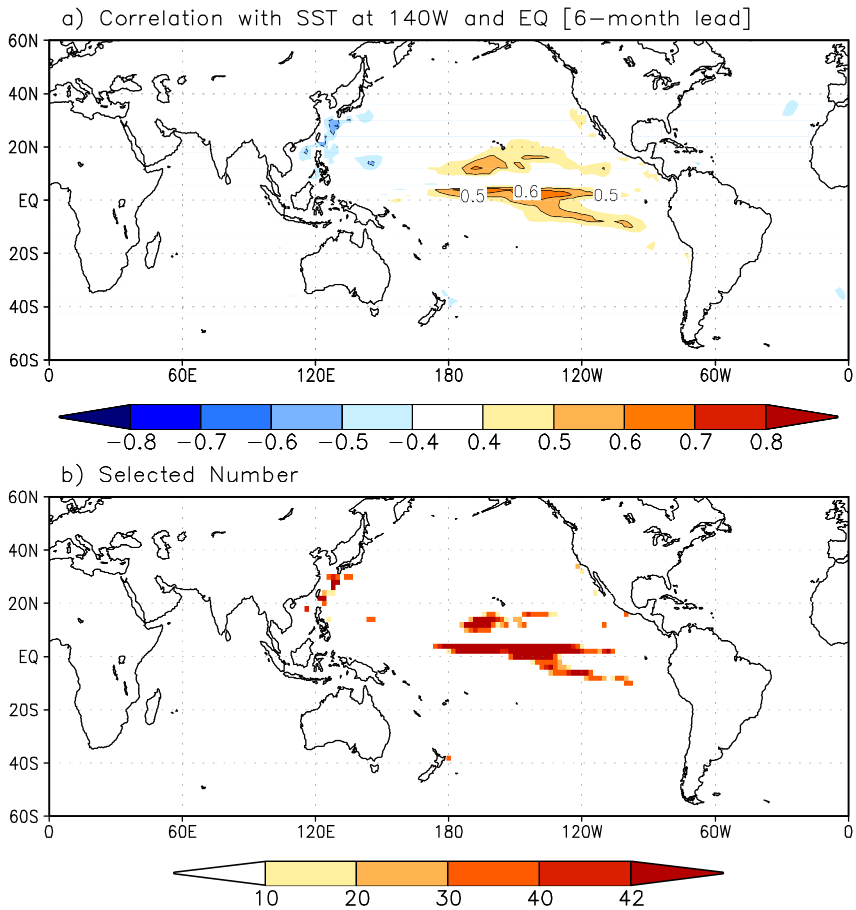

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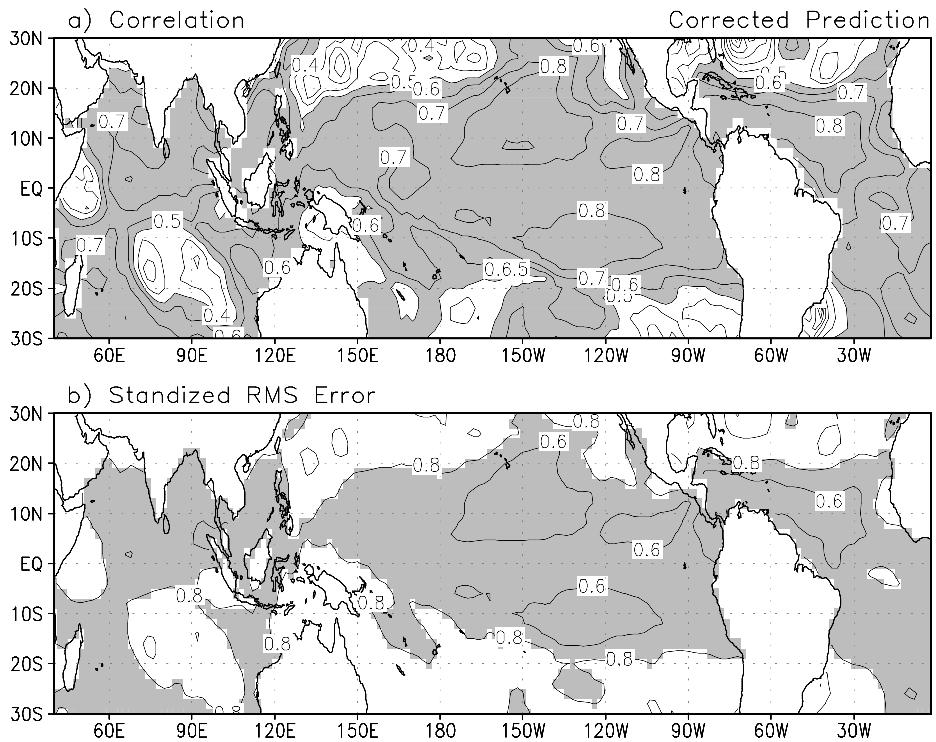

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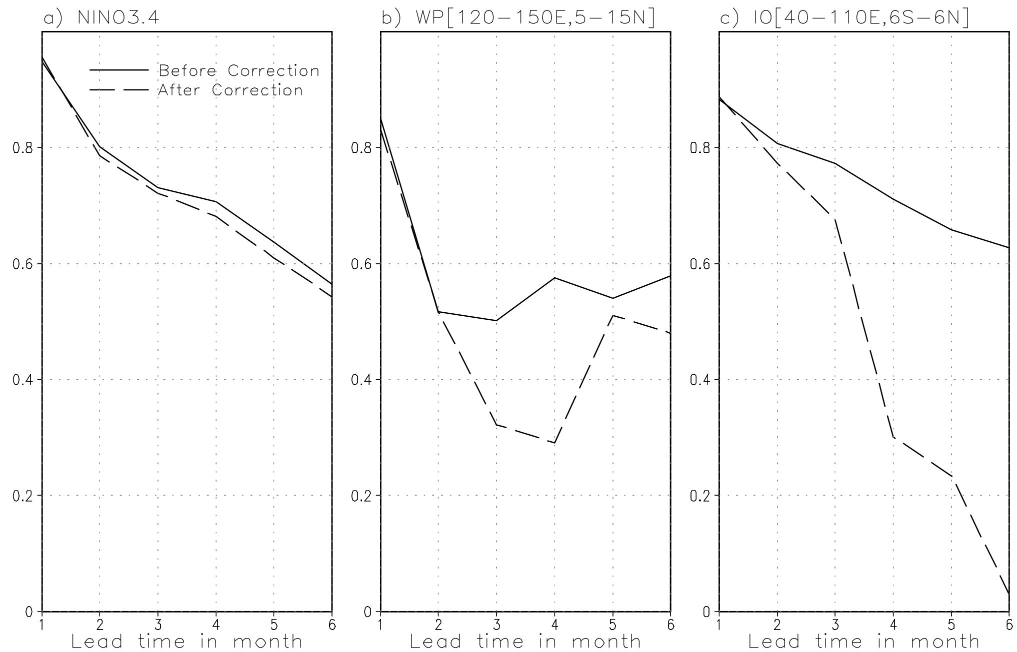

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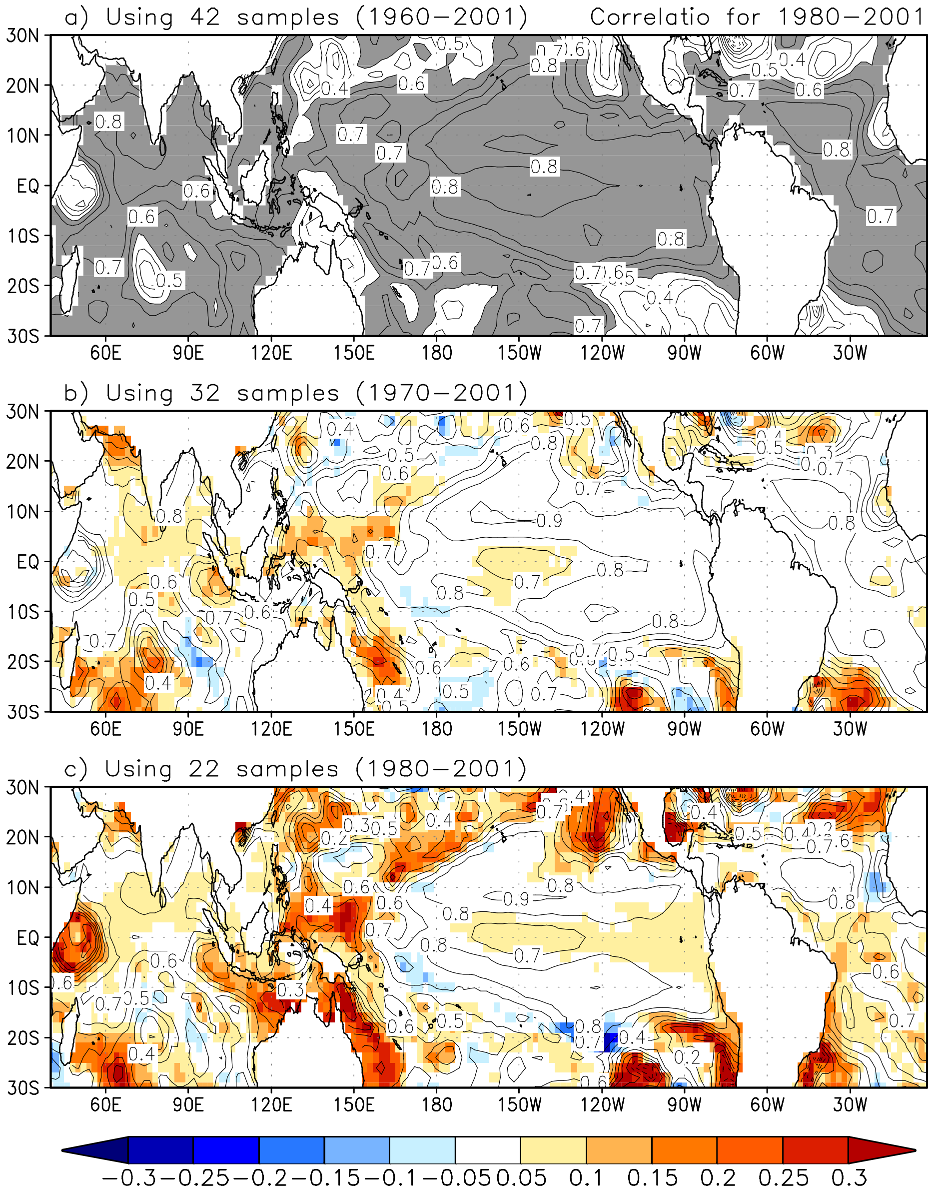

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